

# A Method to Calculate Conserved Currents and Fermionic Force for the Lanczos Approximation to the Overlap Dirac Operator

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## Motivation

- ▶ Derivative of lattice Dirac operator
  - ▶ Fermionic force in HMC
  - ▶ Conserved Currents
- ▶ Overlap Dirac operator:

$$D_{\text{ov}} = \frac{1}{a} (\mathbb{1} + \gamma_5 \text{sgn}[\gamma_5 D_w])$$

- ▶ Numerically challenging
  - ▶ Polynomial/partial fraction approximation
  - ▶ Krylov subspace methods (finite  $\mu$ )

## Motivation

- ▶ Study anomalous transport in dense QCD
- ▶ Overlap Dirac operator at finite chemical potential<sup>a</sup>

$$\gamma_5 D_{\text{ov}}(\mu) \gamma_5 = D_{\text{ov}}(-\mu)$$

- ▶ Conserved currents  $\leftrightarrow$  derivatives over (background) gauge fields:

$$j_\mu^V(x) = \bar{\psi} \frac{\partial D_{\text{ov}}}{\partial \theta_\mu(x)} \psi \quad \dots \quad \theta_\mu \text{ background g.f.}$$

- ▶ Compute approximation to sign function and its derivative for large matrices

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<sup>a</sup>J. Bloch and T. Wettig, Phys.Rev.Lett.97:012003,2006

## Matrix Sign Function

- ▶ Sign function for complex numbers:  $\operatorname{sgn}(z) = \frac{z}{\sqrt{z^2}} = \operatorname{sgn}(\Re(z))$

- ▶ Matrix sign function:

- ▶ Spectral form: ( $\lambda_i$  eigenvalues of  $\mathbf{A}$ )

$$\operatorname{sgn}(\mathbf{A}) = \mathbf{U} \operatorname{sgn}(\mathbf{\Lambda}) \mathbf{U}^{-1}, \quad \operatorname{sgn}(\mathbf{\Lambda}) := \operatorname{diag}(\operatorname{sgn}(\lambda_1), \dots, \operatorname{sgn}(\lambda_n))$$

- ▶ Roberts iteration:

$$\mathbf{X}_{k+1} := \frac{1}{2} (\mathbf{X}_k + \mathbf{X}_k^{-1}), \quad \mathbf{X}_0 = \mathbf{A}$$

(Newton's method for  $\mathbf{X}^2 - \mathbf{1} = \mathbf{0}$ )

- ▶ Both methods numerically very expensive!

## Two-sided Lanczos algorithm

- ▶ Compute approximation to  $\vec{y} = f(\mathbf{A})\vec{x}$ ,  $\mathbf{A} \in \mathbb{C}^{n \times n}$
- ▶ Krylov subspace method:  
 $\mathcal{K}_k(\mathbf{A}, \vec{x}) := \text{span}(\vec{x}, \mathbf{A}\vec{x}, \mathbf{A}^2\vec{x}, \dots, \mathbf{A}^{k-1}\vec{x})$
- ▶ Approximate  $f(\mathbf{A})$  by a polynomial of degree  $k - 1$
- ▶ Information about  $\vec{x}$  taken into account
- ▶ Construct (biorthonormal) matrices  $\mathbf{V}_k$  and  $\mathbf{W}_k \in \mathbb{C}^{n \times k}$  such that

$$\mathbf{A} = \mathbf{V}_k \mathbf{T}_k \mathbf{W}_k^\dagger, \quad \mathbf{T}_k \in \mathbb{C}^{k \times k} \text{ tridiagonal}$$

- ▶ Compute

$$\vec{y} \approx \mathbf{V}_k f(\mathbf{T}_k) \mathbf{W}_k^\dagger \vec{x}$$

**function** LANCZOS( $\mathbf{A}, \vec{x}, k, f$ )

$$\vec{v}_1 \leftarrow \vec{x} / \|\vec{x}\|$$

$$\vec{w}_1 \leftarrow \vec{x} / \|\vec{x}\|$$

**for**  $i \leftarrow 1$  **to**  $k-1$  **do**

$$\mathbf{T}_{ii} \leftarrow \vec{w}_i^\dagger \mathbf{A} \vec{v}_i$$

$$\vec{v}_{i+1} \leftarrow (\mathbf{A} - \mathbf{T}_{ii}) \vec{v}_i$$

$$\vec{w}_{i+1} \leftarrow (\mathbf{A}^\dagger - \mathbf{T}_{ii}^*) \vec{w}_i$$

**if**  $i > 1$  **then**

$$\vec{v}_{i+1} \leftarrow \vec{v}_{i+1} - \mathbf{T}_{(i-1)i} \vec{v}_{i-1}$$

$$\vec{w}_{i+1} \leftarrow \vec{w}_{i+1} - \mathbf{T}_{i(i-1)}^* \vec{w}_{i-1}$$

**end if**

$$\mathbf{T}_{(i+1)i} \leftarrow \|\vec{v}_{i+1}\|$$

$$\mathbf{T}_{i(i+1)} \leftarrow \vec{w}_{i+1}^\dagger \vec{v}_{i+1}$$

$$\mathbf{T}_{i(i+1)} \leftarrow \mathbf{T}_{i(i+1)} / \mathbf{T}_{(i+1)i}$$

$$\vec{v}_{i+1} \leftarrow \vec{v}_{i+1} / \mathbf{T}_{(i+1)i}$$

$$\vec{w}_{i+1} \leftarrow \vec{w}_{i+1} / \mathbf{T}_{i(i+1)}^*$$

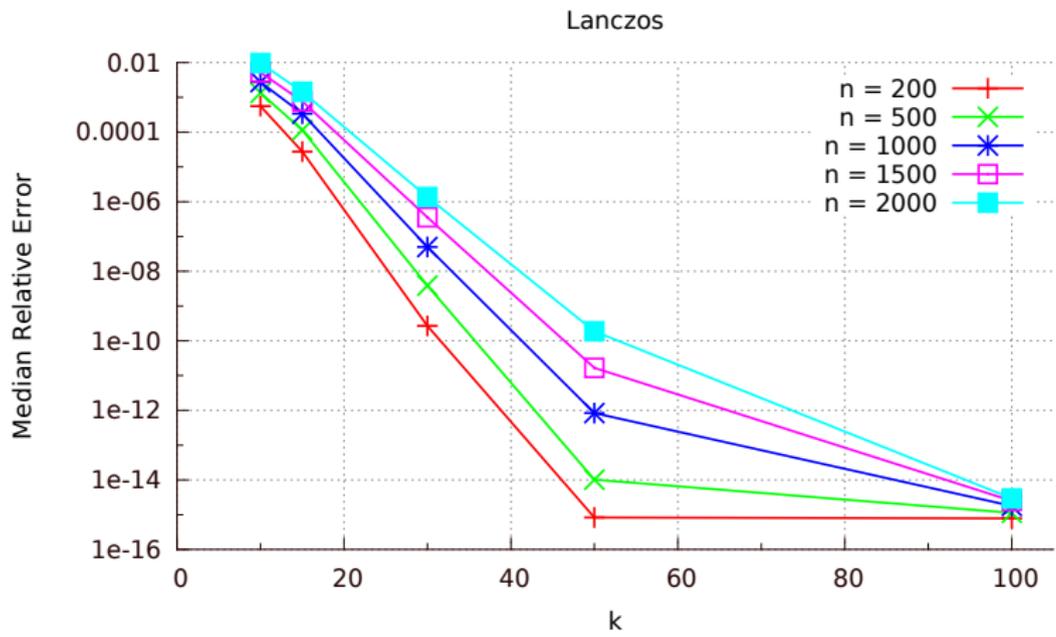
**end for**

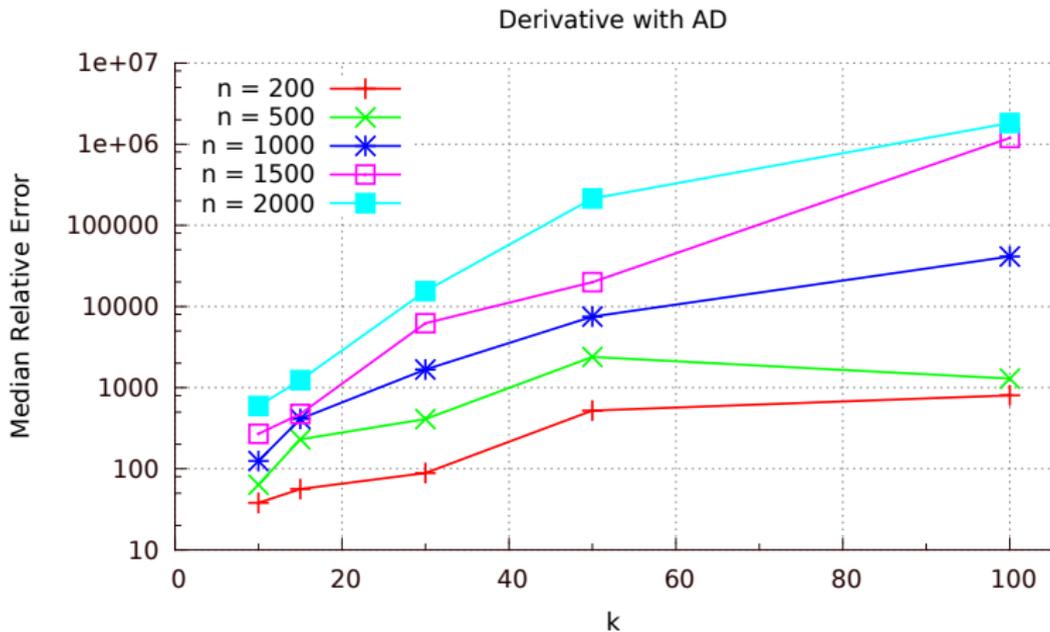
$$\mathbf{T}_{kk} \leftarrow \vec{w}_k^\dagger \mathbf{A} \vec{v}_k$$

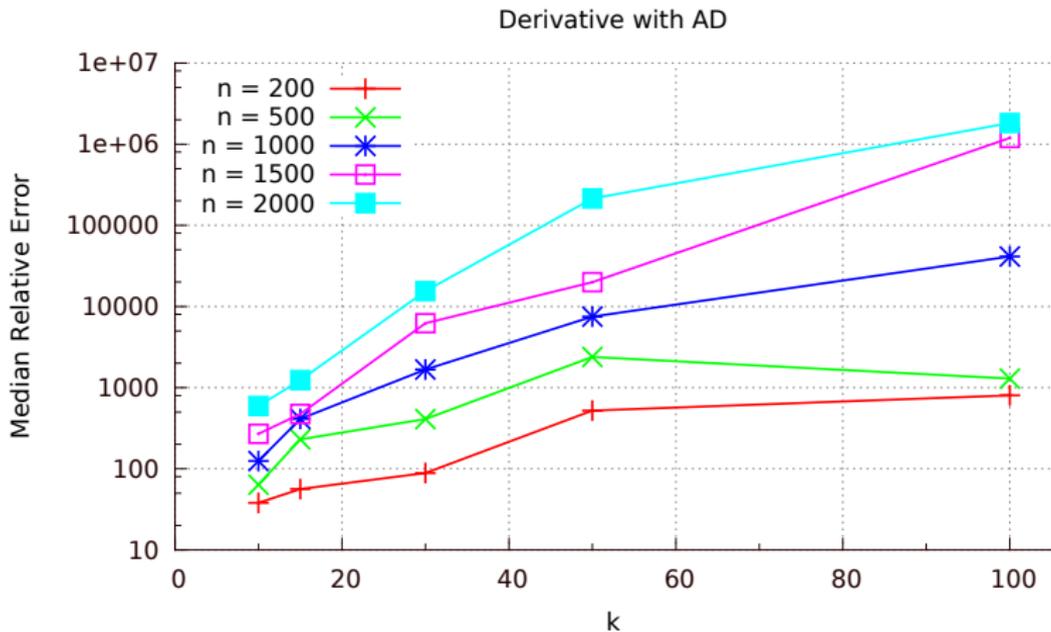
**return**  $\|\vec{x}\| \mathbf{V} f(\mathbf{T}) \hat{e}_1$

**end function**

- ▶  $\mathbf{A}$  only in matrix-vector multiplication
- ▶ Approximation depends on  $\vec{x}$
- ▶ Compute  $f$  only for  $\mathbf{T} \in \mathbb{C}^{k \times k}$
- ▶ Since  $\vec{w}_1 = \vec{x} / \|\vec{x}\|$ :
 
$$\mathbf{W}^\dagger \vec{x} = \hat{e}_1$$
- ▶ Operations:  $\mathcal{O}(nk) + \mathcal{O}(k^3)$







- ▶ Large errors even for small matrix sizes
- ▶ Lanczos AD numerically unstable

A hint from A. Frommer:

### Theorem (R. Mathias<sup>b</sup>)

Let  $\mathbf{A}(t) \in \mathbb{C}^{n \times n}$  be differentiable at  $t = 0$  and assume that the spectrum of  $\mathbf{A}(t)$  is contained in an open subset  $\mathcal{D} \subset \mathbb{C}$  for all  $t$  in some neighbourhood of 0. Let  $f$  be  $2n - 1$  times continuously differentiable on  $\mathcal{D}$ . We then have:

$$f \left( \begin{bmatrix} \mathbf{A}(0) & \dot{\mathbf{A}}(0) \\ 0 & \mathbf{A}(0) \end{bmatrix} \right) \equiv \begin{bmatrix} f(\mathbf{A}(0)) & \left. \frac{d}{dt} f(\mathbf{A}(t)) \right|_{t=0} \\ 0 & f(\mathbf{A}(0)) \end{bmatrix}$$

<sup>b</sup>R. Mathias, SIAM J. Matrix Anal. Appl., 17(3):610-620,1996

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We can compute the derivative of  $f(\mathbf{A})$  without knowing  $f'(\mathbf{A})!$

## For polynomials

Let  $p_n(\bar{\mathbf{A}}) = \bar{\mathbf{A}}^n$

$n = 2$ :

$$p_2(\bar{\mathbf{A}}) = \begin{bmatrix} \mathbf{A} & \dot{\mathbf{A}} \\ 0 & \mathbf{A} \end{bmatrix}^2 = \begin{bmatrix} \mathbf{A}^2 & \mathbf{A}\dot{\mathbf{A}} + \dot{\mathbf{A}}\mathbf{A} \\ 0 & \mathbf{A}^2 \end{bmatrix} = \begin{bmatrix} p_2(\mathbf{A}) & \dot{p}_2(\mathbf{A}) \\ 0 & p_2(\mathbf{A}) \end{bmatrix}$$

$n \rightarrow n + 1$ :

$$p_{n+1}(\bar{\mathbf{A}}) = \begin{bmatrix} p_n(\mathbf{A}) & \dot{p}_n(\mathbf{A}) \\ 0 & p_n(\mathbf{A}) \end{bmatrix} \begin{bmatrix} \mathbf{A} & \dot{\mathbf{A}} \\ 0 & \mathbf{A} \end{bmatrix} = \begin{bmatrix} p_{n+1}(\mathbf{A}) & \dot{p}_{n+1}(\mathbf{A}) \\ 0 & p_{n+1}(\mathbf{A}) \end{bmatrix}$$

## General proof

Let  $\varepsilon \neq 0$  and  $\mathbf{U} = \begin{bmatrix} \mathbb{1} & \varepsilon^{-1}\mathbb{1} \\ 0 & \mathbb{1} \end{bmatrix}$ .

Since  $f(\mathbf{XAX}^{-1}) = \mathbf{X}f(\mathbf{A})\mathbf{X}^{-1}$  we get:

$$\begin{aligned} f\left(\begin{bmatrix} \mathbf{A}(0) & \frac{\mathbf{A}(\varepsilon)-\mathbf{A}(0)}{\varepsilon} \\ 0 & \mathbf{A}(\varepsilon) \end{bmatrix}\right) &= \mathbf{U}f\left(\mathbf{U}^{-1}\begin{bmatrix} \mathbf{A}(0) & \frac{\mathbf{A}(\varepsilon)-\mathbf{A}(0)}{\varepsilon} \\ 0 & \mathbf{A}(\varepsilon) \end{bmatrix}\mathbf{U}\right)\mathbf{U}^{-1} \\ &= \mathbf{U}f\left(\begin{bmatrix} \mathbf{A}(0) & 0 \\ 0 & \mathbf{A}(\varepsilon) \end{bmatrix}\right)\mathbf{U}^{-1} \\ &= \mathbf{U}\begin{bmatrix} f(\mathbf{A}(0)) & 0 \\ 0 & f(\mathbf{A}(\varepsilon)) \end{bmatrix}\mathbf{U}^{-1} \\ &= \begin{bmatrix} f(\mathbf{A}(0)) & \frac{f(\mathbf{A}(\varepsilon))-f(\mathbf{A}(0))}{\varepsilon} \\ 0 & f(\mathbf{A}(\varepsilon)) \end{bmatrix} \end{aligned}$$

Take  $\lim_{\varepsilon \rightarrow 0}$  on both sides.

- ▶ Useful for numerical calculations?

- ▶ Advantage:

- ▶ Compute derivative with Lanczos algorithm:

$$\text{sign} \left( \begin{bmatrix} \mathbf{A} & \dot{\mathbf{A}} \\ 0 & \mathbf{A} \end{bmatrix} \right) \begin{pmatrix} 0 \\ \vec{x} \end{pmatrix} = \begin{pmatrix} \frac{d}{dt} \text{sign}(\mathbf{A})\vec{x} \\ \text{sign}(\mathbf{A})\vec{x} \end{pmatrix}$$

- ▶ Disadvantage:

- ▶ Size of linear space doubles

- ▶ Convergence of Lanczos  $\rightarrow$  spectrum of  $\bar{\mathbf{A}} := \begin{bmatrix} \mathbf{A} & \dot{\mathbf{A}} \\ 0 & \mathbf{A} \end{bmatrix}$ ?

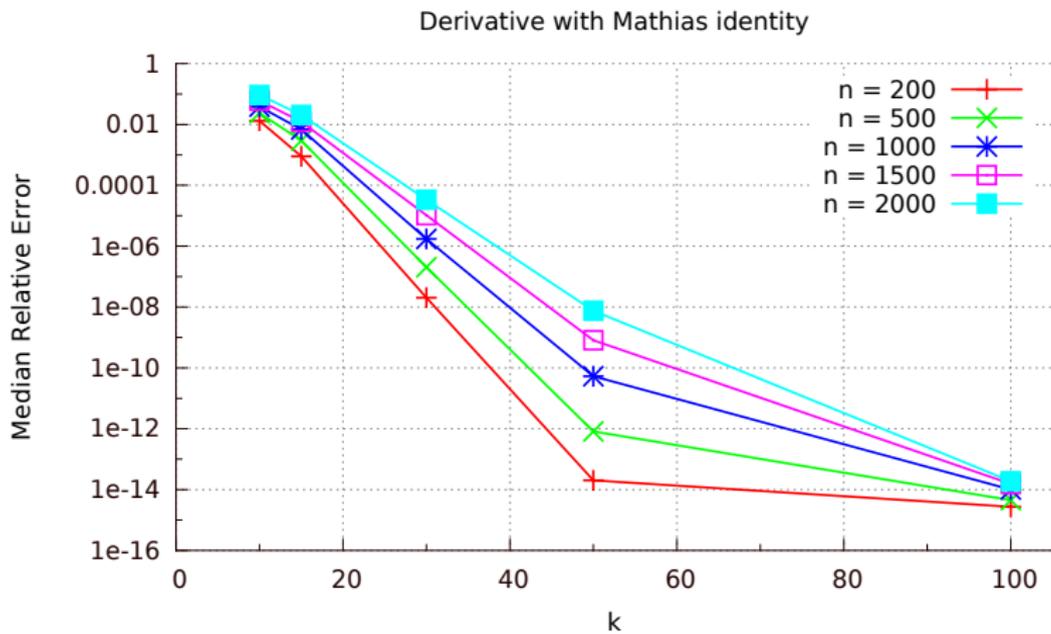
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## Properties of $\bar{A}$

- ▶  $\det \bar{A} = (\det A)^2$
- ▶  $\lambda$  eigenvalue of  $\bar{A} \Leftrightarrow \lambda$  eigenvalue of  $A$
- ▶  $\vec{x} := \begin{pmatrix} \vec{x}_1 \\ \vec{x}_2 \end{pmatrix}$  eigenvector of  $\bar{A}$  to eigenvalue  $\lambda$ , then:
  - $\vec{x}_2 \equiv 0$  and  $\vec{x}_1$  eigenvector of  $A$  to eigenvalue  $\lambda$
  - or**
  - $\vec{x}_2$  eigenvector of  $A$  to eigenvalue  $\lambda$  and  $\vec{x}_1 = \frac{\partial}{\partial t} \vec{x}_2$



## Derivative of the Overlap operator

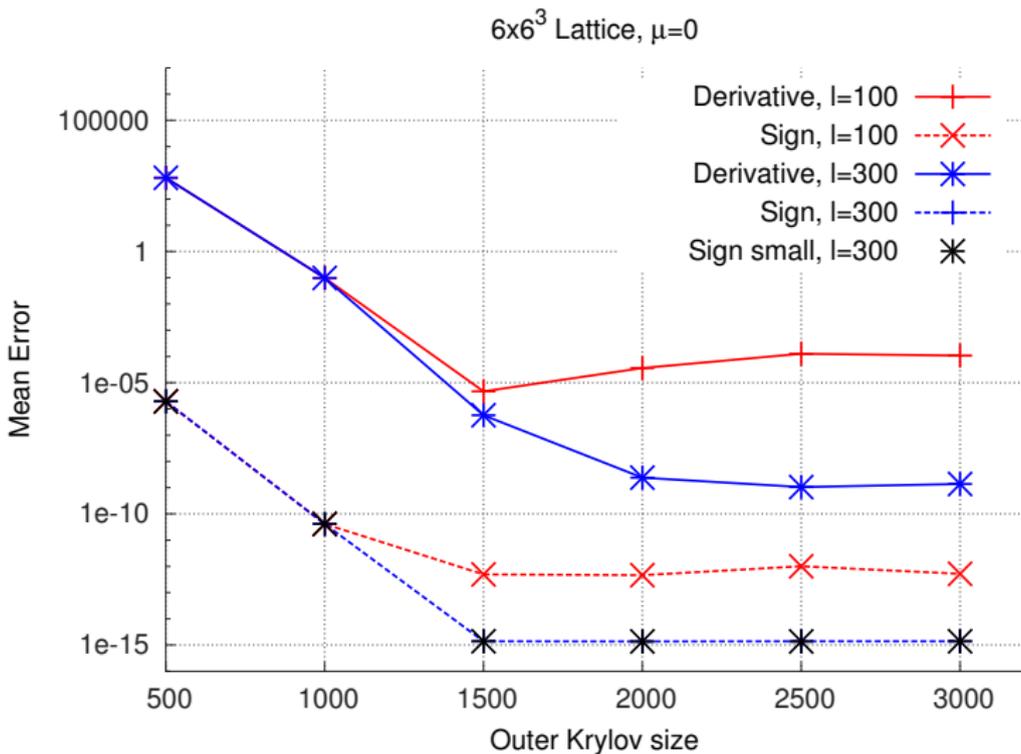
- ▶ Lattice size  $6 \times 6^3$
- ▶ SU(3) configurations<sup>c</sup> with improved action
  - ▶  $\beta = 5.95, \rho = 1.4$
- ▶ No deflation (yet)
- ▶ Nested Lanczos algorithm<sup>d</sup>  $\rightarrow$  inner Krylov size  $l$  fixed
- ▶ Results for

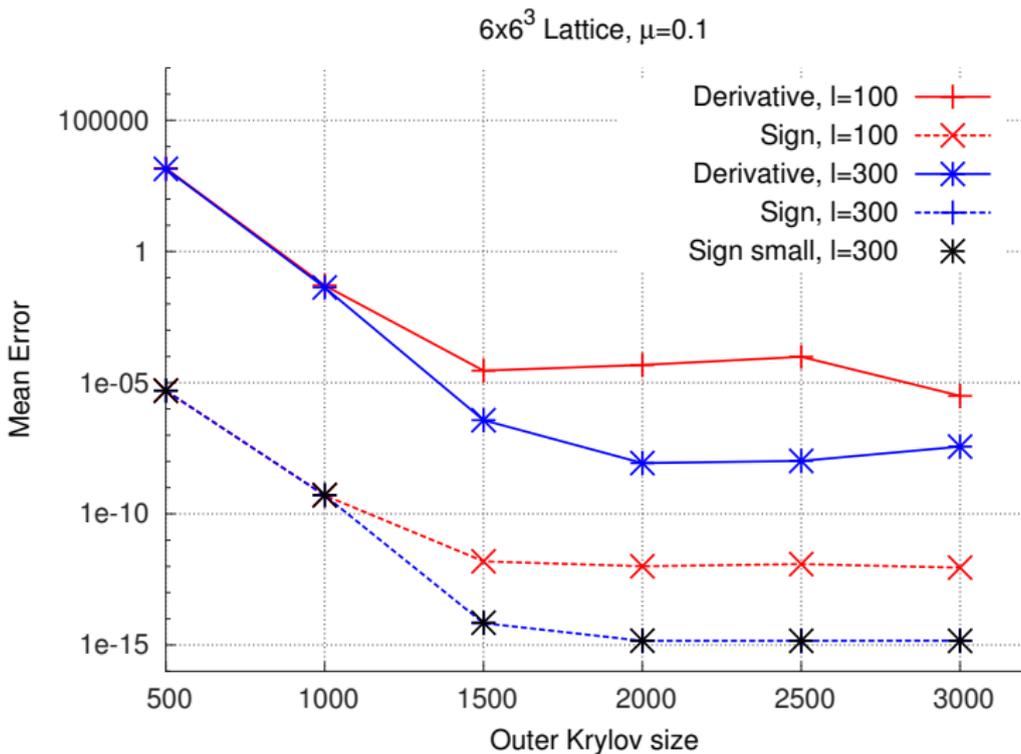
$$\text{sgn}(\gamma_5 D_W) \quad \text{and} \quad \frac{\partial}{\partial \theta_\mu(x)} \text{sgn}(\gamma_5 D_W)$$

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<sup>c</sup> Provided by Oleg Kochetkov

<sup>d</sup> J. Bloch and S. Heybrock, Comput.Phys.Commun.182:878-889,2011





## Summary and Outlook

- ▶ Summary
  - ▶ A method to compute derivatives of the Overlap operator
  - ▶ Test on small lattices
  - ▶ First results are very promising
- ▶ Outlook
  - ▶ Implement deflation
  - ▶ Generalization to higher derivatives
  - ▶ Application to physical problems